Iris_Dataset_Classification

In [2]:
```
import pandas as pd
import numpy as np
import os
import matplotlib.pyplot as plt
import seaborn as sns
from sklearn.model_selection import train_test_split
from sklearn.tree import DecisionTreeClassifier
import pickle
import warnings  # Import the warnings module
warnings.filterwarnings('ignore')
```

Loading the dataset

In [3]:
```
df = pd.read_csv('Iris.csv')
df.head()
```

Out[3]:

	Id	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	1	5.1	3.5	1.4	0.2	Iris-setosa
1	2	4.9	3.0	1.4	0.2	Iris-setosa
2	3	4.7	3.2	1.3	0.2	Iris-setosa
3	4	4.6	3.1	1.5	0.2	Iris-setosa
4	5	5.0	3.6	1.4	0.2	Iris-setosa

In [4]:
```
# delete a column
df = df.drop(columns = ['Id'])
df.head()
```

Out[4]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm	Species
0	5.1	3.5	1.4	0.2	Iris-setosa
1	4.9	3.0	1.4	0.2	Iris-setosa
2	4.7	3.2	1.3	0.2	Iris-setosa
3	4.6	3.1	1.5	0.2	Iris-setosa
4	5.0	3.6	1.4	0.2	Iris-setosa

In [5]:
```
# to display stats about data
df.describe()
```

Out[5]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
count	150.000000	150.000000	150.000000	150.000000
mean	5.843333	3.054000	3.758667	1.198667
std	0.828066	0.433594	1.764420	0.763161
min	4.300000	2.000000	1.000000	0.100000
25%	5.100000	2.800000	1.600000	0.300000
50%	5.800000	3.000000	4.350000	1.300000
75%	6.400000	3.300000	5.100000	1.800000
max	7.900000	4.400000	6.900000	2.500000

In [6]:
```
# to basic info about datatype
df.info()
```

```
<class 'pandas.core.frame.DataFrame'>
RangeIndex: 150 entries, 0 to 149
Data columns (total 5 columns):
 #   Column         Non-Null Count  Dtype  
---  ------         --------------  -----  
 0   SepalLengthCm  150 non-null    float64
 1   SepalWidthCm   150 non-null    float64
 2   PetalLengthCm  150 non-null    float64
 3   PetalWidthCm   150 non-null    float64
 4   Species        150 non-null    object 
dtypes: float64(4), object(1)
memory usage: 6.0+ KB
```

In [7]:
```
# to display no. of samples on each class
df['Species'].value_counts()
```

Out[7]:
```
Iris-setosa        50
Iris-versicolor    50
Iris-virginica     50
Name: Species, dtype: int64
```

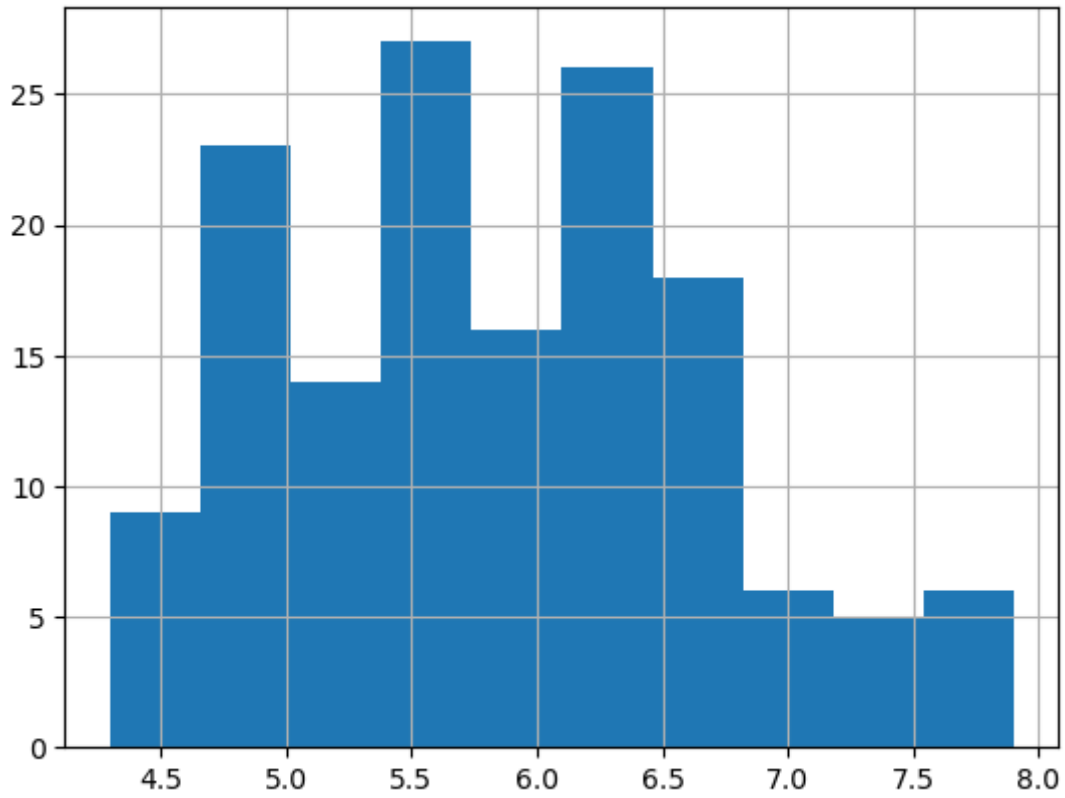
Preprocessing the dataset

In [8]:
```
# check for null values
df.isnull().sum()
```

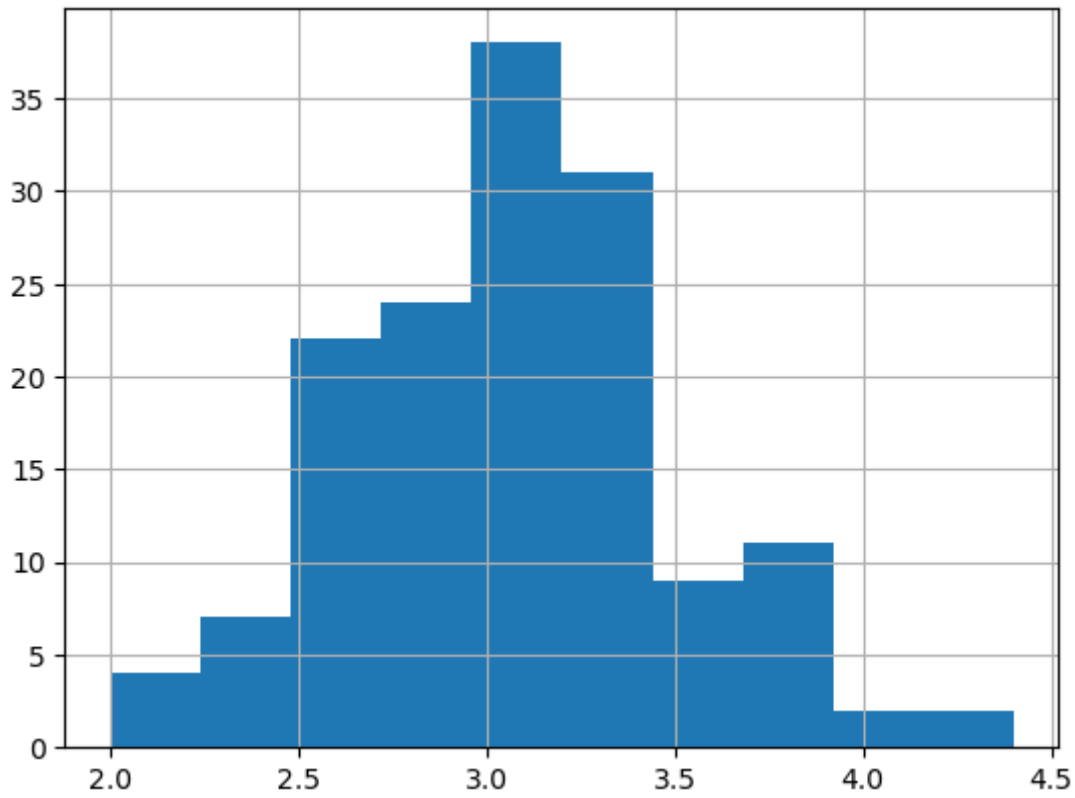
Out[8]:
```
SepalLengthCm    0
SepalWidthCm     0
PetalLengthCm    0
PetalWidthCm     0
Species          0
dtype: int64
```

Exploratory Data Analysis

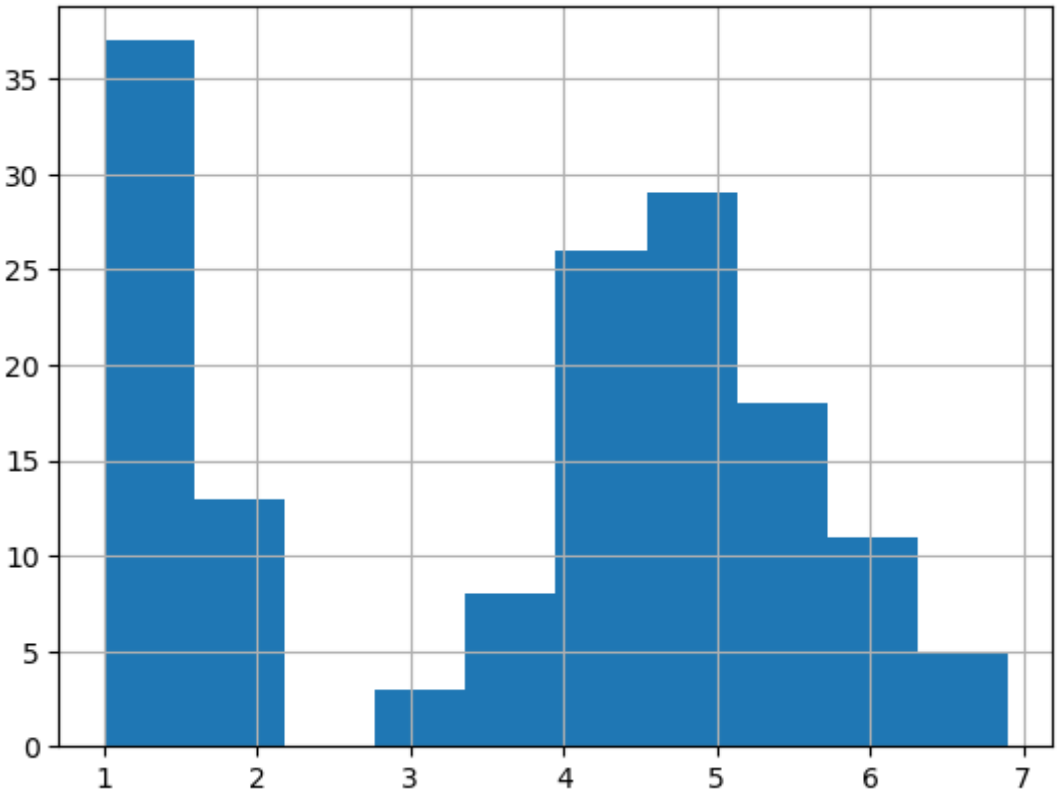
In [9]:
```
# histograms
df['SepalLengthCm'].hist()
plt.show()
```



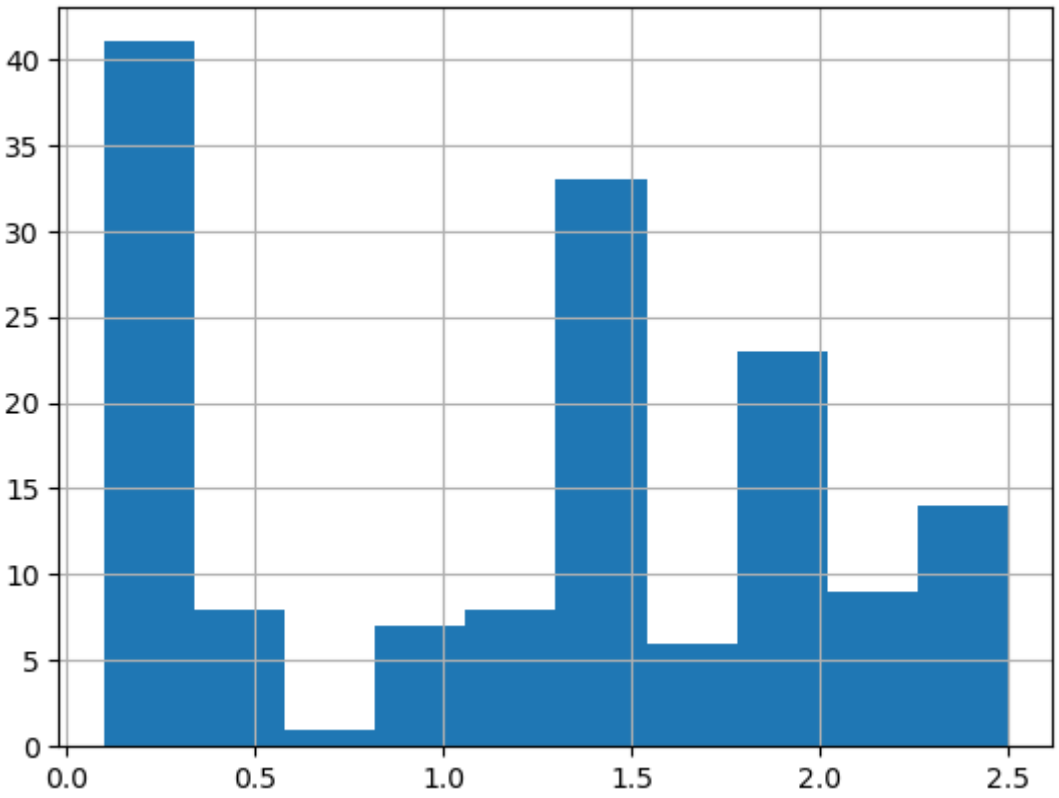
In [10]:
```
df['SepalWidthCm'].hist()
plt.show()
```



In [11]:
```
df['PetalLengthCm'].hist()
plt.show()
```

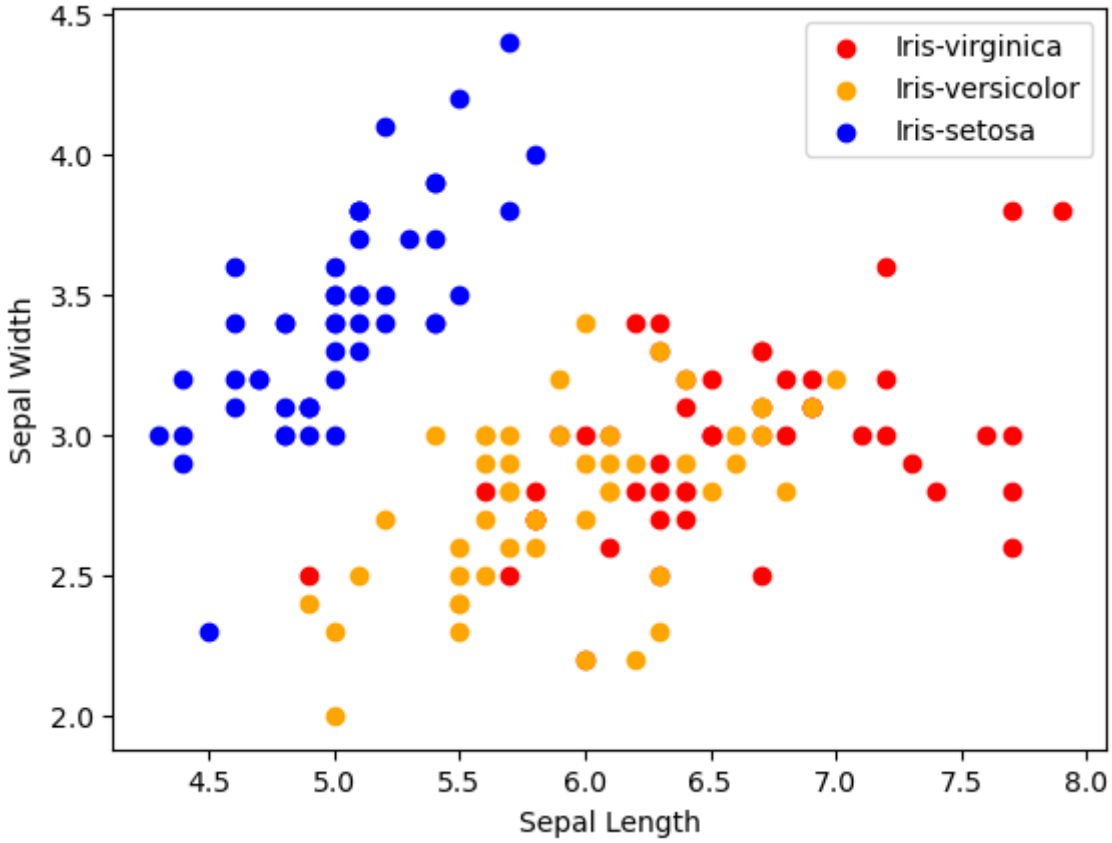


In [12]:
```
df['PetalWidthCm'].hist()
plt.show()
```

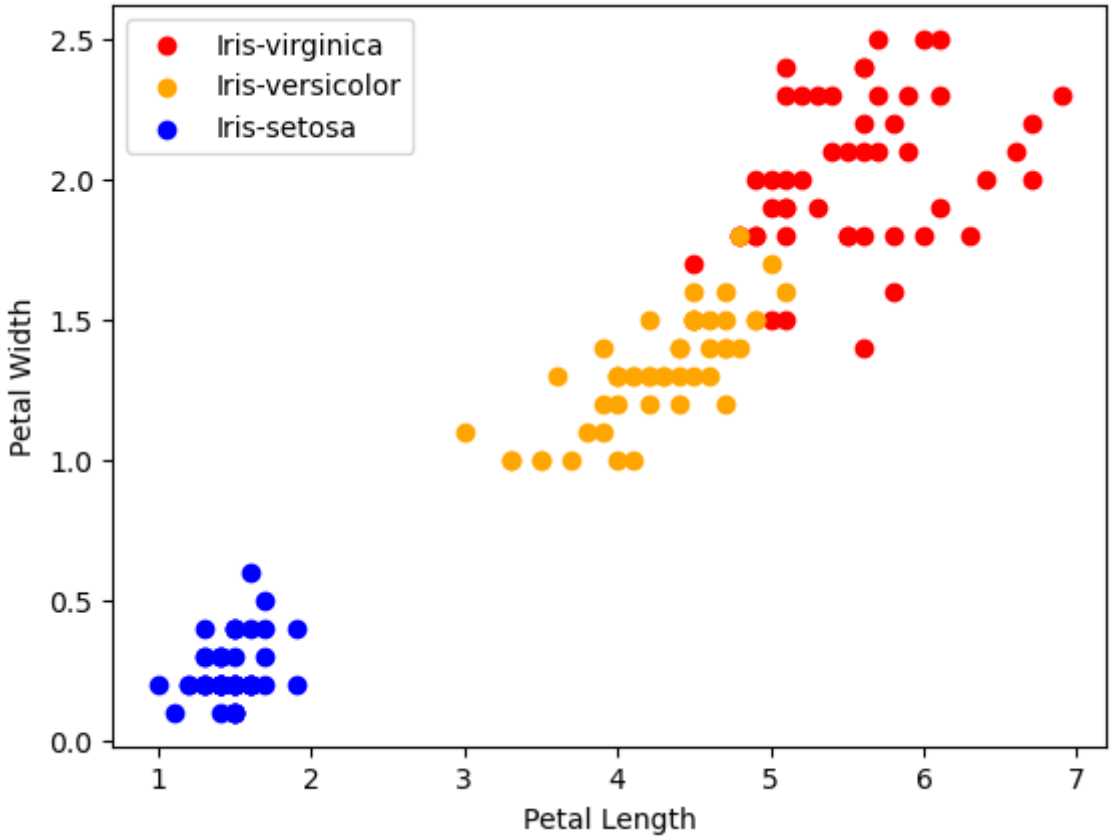


In [13]:
```
# scatterplot
colors = ['red', 'orange', 'blue']
species = ['Iris-virginica','Iris-versicolor','Iris-setosa']
```

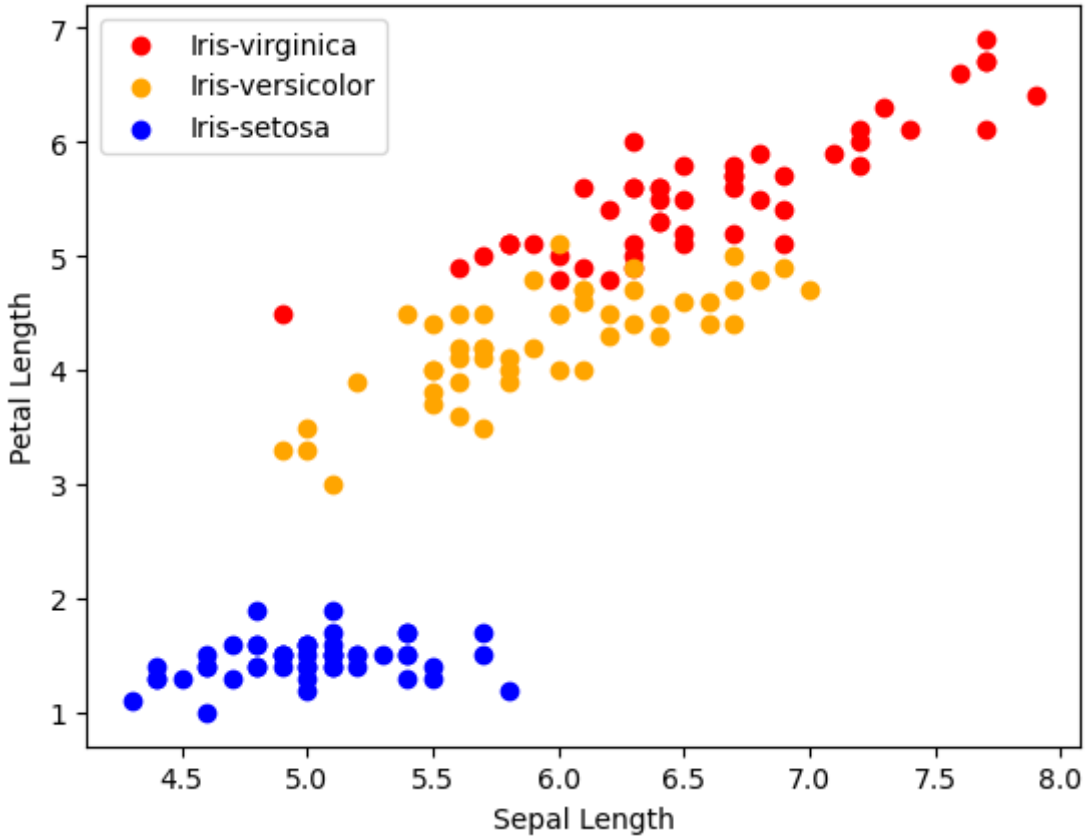
In [14]:
```
for i in range(3):
    x = df[df['Species'] == species[i]]
    plt.scatter(x['SepalLengthCm'], x['SepalWidthCm'], c = colors[i], label=
plt.xlabel("Sepal Length")
plt.ylabel("Sepal Width")
plt.legend()
plt.show()
```



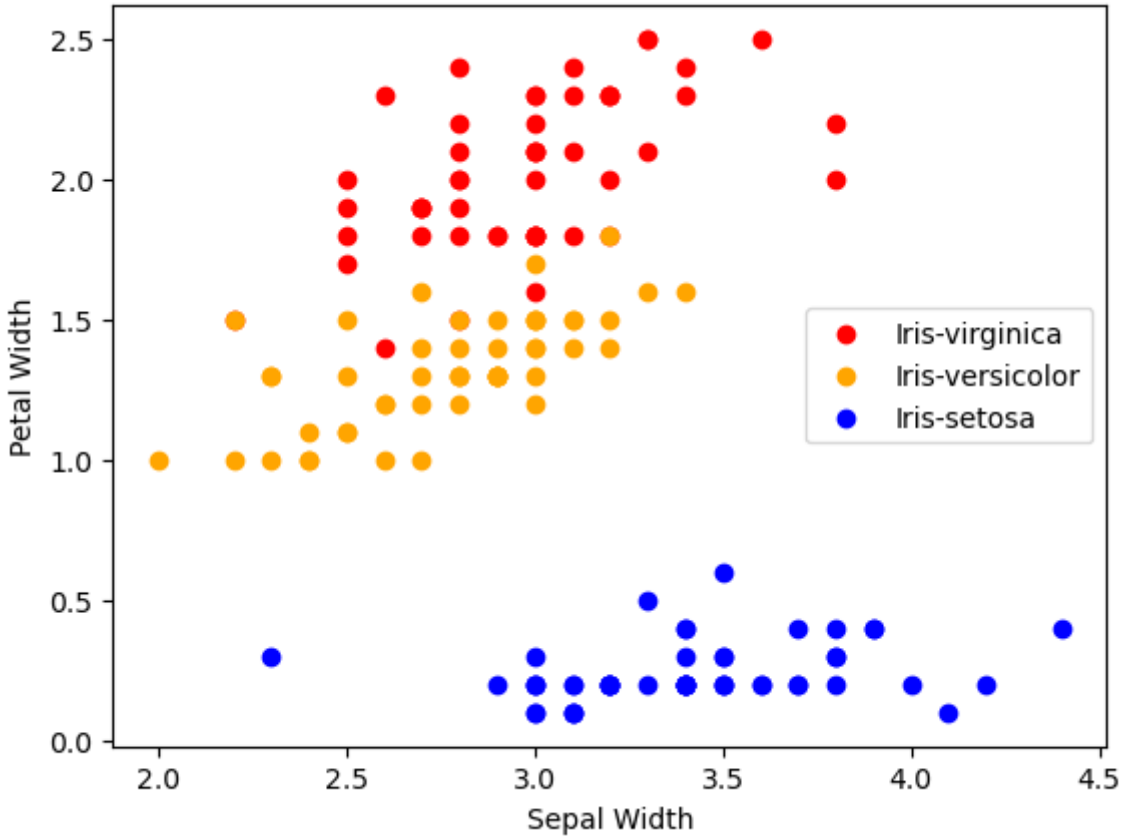
In [15]:
```
for i in range(3):
    x = df[df['Species'] == species[i]]
    plt.scatter(x['PetalLengthCm'], x['PetalWidthCm'], c = colors[i], label=
plt.xlabel("Petal Length")
plt.ylabel("Petal Width")
plt.legend()
plt.show()
```



In [16]:
```
for i in range(3):
    x = df[df['Species'] == species[i]]
    plt.scatter(x['SepalLengthCm'], x['PetalLengthCm'], c = colors[i], label
plt.xlabel("Sepal Length")
plt.ylabel("Petal Length")
plt.legend()
plt.show()
```



In [17]:
```
for i in range(3):
    x = df[df['Species'] == species[i]]
    plt.scatter(x['SepalWidthCm'], x['PetalWidthCm'], c = colors[i], label=s
plt.xlabel("Sepal Width")
plt.ylabel("Petal Width")
plt.legend()
plt.show()
```



Coorelation Matrix

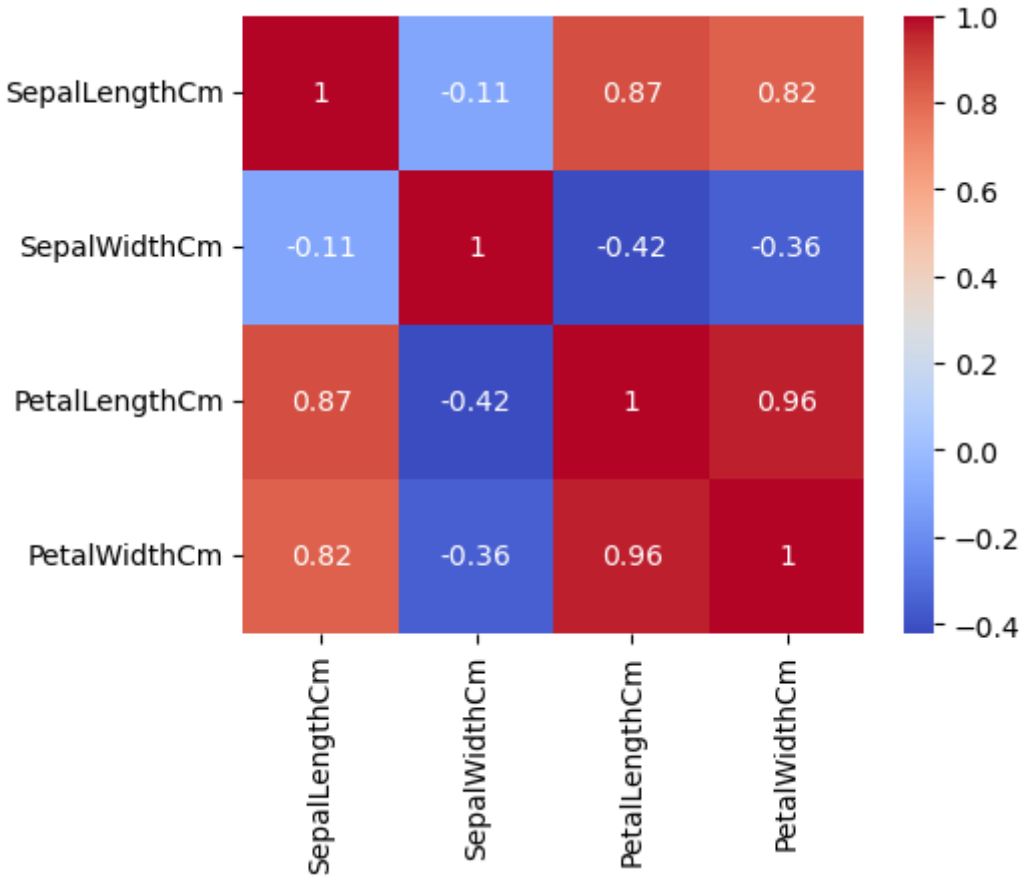
A correlation matrix is a table showing correlation coefficients between variables. Each cell in the table shows the correlation between two variables. The value is in the range of -1 to 1. If two varibles have high correlation, we can neglect one variable from those two.

In [18]:
```
df.corr()
```

Out[18]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
SepalLengthCm	1.000000	-0.109369	0.871754	0.817954
SepalWidthCm	-0.109369	1.000000	-0.420516	-0.356544
PetalLengthCm	0.871754	-0.420516	1.000000	0.962757
PetalWidthCm	0.817954	-0.356544	0.962757	1.000000

In [19]:
```
corr = df.corr()
fig, ax = plt.subplots(figsize=(5,4))
sns.heatmap(corr, annot=True, ax=ax, cmap = 'coolwarm')
plt.show()
```



Label Encoder

In machine learning, we usually deal with datasets which contains multiple labels in one or more than one columns. These labels can be in the form of words or numbers. Label Encoding refers to converting the labels into numeric form so as to convert it into the machine-readable form

In [20]:
```
# from sklearn.preprocessing import LabelEncoder
# le = LabelEncoder()
```

In [21]:
```
#df['Species'] = le.fit_transform(df['Species'])
#df.head()
```

Model Training

In [22]:
```
from sklearn.model_selection import train_test_split
# train - 70
# test - 30
X = df.drop(columns=['Species'])
Y = df['Species']
x_train, x_test, y_train, y_test = train_test_split(X, Y, test_size=0.30)
```

In [23]:
```
# logistic regression
from sklearn.linear_model import LogisticRegression
model = LogisticRegression()
```

In [24]:
```
# model training
model.fit(x_train, y_train)
```

Out[24]:
```
LogisticRegression()
```

In [25]:
```
# print metric to get performance
print("Accuracy: ",model.score(x_test, y_test) * 100)
```

```
Accuracy:  97.77777777777777
```

In [26]:
```
# knn - k-nearest neighbours
from sklearn.neighbors import KNeighborsClassifier
model = KNeighborsClassifier()
```

In [27]:
```
model.fit(x_train, y_train)
```

Out[27]:
```
KNeighborsClassifier()
```

In [28]:
```
# print metric to get performance
print("Accuracy: ",model.score(x_test, y_test) * 100)
```

```
Accuracy:  97.77777777777777
```

In [29]:
```
# decision tree
from sklearn.tree import DecisionTreeClassifier
model = DecisionTreeClassifier()
```

In [30]:
```
model.fit(x_train, y_train)
```

Out[30]:
```
DecisionTreeClassifier()
```

In [32]:
```
# print metric to get performance
print("Accuracy: ",model.score(x_test, y_test) * 100)
```

```
Accuracy:  97.77777777777777
```

In [33]:
```
# save the model
import pickle
filename = 'savedmodel.sav'
pickle.dump(model, open(filename, 'wb'))
```

In [34]:
```
x_test.head()
```

Out[34]:

	SepalLengthCm	SepalWidthCm	PetalLengthCm	PetalWidthCm
16	5.4	3.9	1.3	0.4
120	6.9	3.2	5.7	2.3
148	6.2	3.4	5.4	2.3
61	5.9	3.0	4.2	1.5
22	4.6	3.6	1.0	0.2

In [35]:
```
load_model = pickle.load(open(filename,'rb'))
```

In [36]:
```
load_model.predict([[6.0, 2.2, 4.0, 1.0]])
```

Out[36]:
```
array(['Iris-versicolor'], dtype=object)
```

THANK YOU!

GitHub: https://github.com/anujtiwari21?tab=repositories (https://github.com/anujtiwari21?tab=repositories)